Efficient globally optimal segmentation of cells in fluorescence microscopy images using level sets and convex energy functionals

— Medical Image Analysis —

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Article presentation

- *Efficient globally optimal segmentation of cells in fluorescence microscopy images using level sets and convex energy functionals*
- Jan-Philip Bergeest, Karl Rohr, University of Heidelberg, 2012

Article presentation

- *Efficient globally optimal segmentation of cells in fluorescence microscopy images using level sets and convex energy functionals*
- Jan-Philip Bergeest, Karl Rohr, University of Heidelberg, 2012
- Article content:
  - Implicit method based on level set functions and active contour energy functions.
  - Split Bregman algorithm paired with Gauss Seidel
  - Solutions for: Intensity inhomogeneities, convex problem solving
  - 3 step and 2 step approaches

Level set approach

- ϕ_n define a contour along the border
- $$\phi_n = \begin{cases} > 0 & \text{in foreground,} \\ < 0 & \text{in background,} \\ = 0 & \text{in object boundary} \end{cases}$$
- Iteratively updated by minimizing the energy function:

$$\min_{0\leq\phi_n\leq 1} E_j^c(\Theta, \phi_n) = \min_{0\leq\phi_n\leq 1} \underbrace{\lambda < \phi_n, r_j >}_{\text{Data fidelity}} + \underbrace{|\nabla\phi_n|_1}_{\textit{Regularization}} \tag{1}$$

- Energy functions: guide the evolution of the level set function

$$\underset{0\leq\phi_n\leq 1, \vec{d}}{\arg\min} \left(\lambda < \phi_n, r_j > + |\vec{d}|_1 + \frac{\nu}{2} ||\vec{d} - \nabla\phi_n - \vec{b}||_2^2 \right) \tag{2}$$

$$\Delta\phi_n(x) = \frac{\lambda}{\nu} r_j + \nabla \cdot (\vec{d} - \vec{b}) \tag{3}$$

Split Bregman's Algorithm

Algorithm 1 Split Bregman's Algorithm

while $\|\phi^k - \phi^{k-1}\| > \epsilon$ **do**

Define r^{k-1} as the energy function for the level set ϕ_n^{k-1}

$\phi_n^k = GS_{GSC}(r^{k-1}, \vec{d}^{k-1}, \vec{b}^{k-1})$

$\vec{d}^k = \text{shrink}(\nabla\phi_n^k + \vec{b}^{k-1}, \nu)$

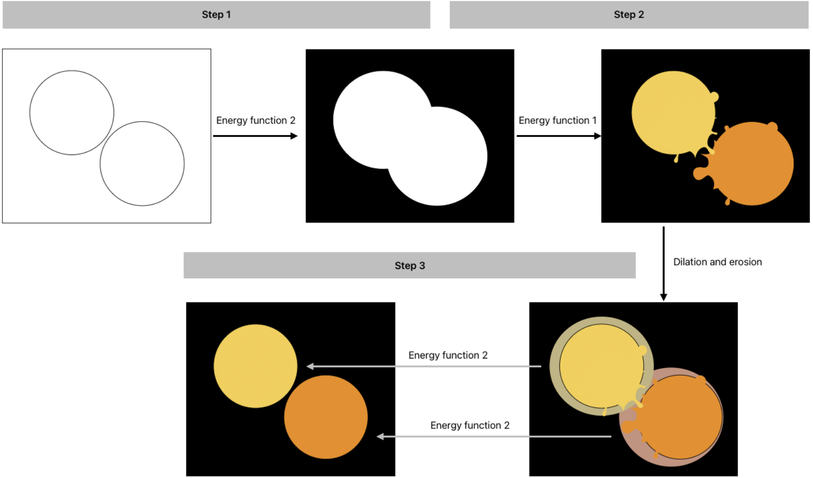
$\vec{b}^k = \vec{b}^{k-1} + \nabla\phi_n^k - \vec{d}^k$

Find $\Omega^k = \{x : \phi_n^k(x) > 0\}$

Update μ_0 and μ_1 (and σ_0, σ_1)

end while

Step-by-step implementations: 3 steps



Energy functions

$$E_1(\Theta, \partial\Omega) = \lambda(\sum_{i=0}^{1} \kappa_i(\int_{\Omega_i} I(x) - \mu_i)^2 dx) + Per(\Omega_1)$$

$$\underset{Reformulation}{\longrightarrow} \; r_1 = \kappa_1(I(x) - \mu_1)^2 - \kappa_0(I(x) - \mu_0)^2$$

Energy functions

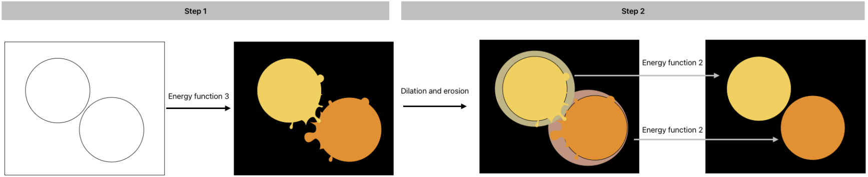
$$E_1(\Theta, \partial\Omega) = \lambda(\sum_{i=0}^{1} \kappa_i(\int_{\Omega_i} I(x) - \mu_i)^2 dx) + Per(\Omega_1)$$

$$\underset{Reformulation}{\longrightarrow} r_1 = \kappa_1(I(x) - \mu_1)^2 - \kappa_0(I(x) - \mu_0)^2$$

$$E_2(\Theta, \partial\Omega) = \lambda(\sum_{i=0}^{1} \int_{\Omega_i} -log(P(I(x)|\Omega_i))dx) + Per(\Omega_1)$$

$$\underset{Reformulation}{\longrightarrow} r_2 = log(P(I(x)|\Omega_1) - log(P(I(x)|\Omega_0)$$

Step-by-step implementations: 2 steps



Energy functions

$$E_3(\Theta, \partial\Omega) = \lambda(\sum_{i=0}^{1} \kappa_i \int_{\Omega_i} \int_{\Omega_1} K_\sigma(x-y)|I(y) - f_i(x)|^2 dydx) + Per(\Omega_1)$$

$$\underset{Reformulation}{\longrightarrow} r_3 = \sum_{i=0}^{1} (-1)^i \kappa_i \int K_\sigma(y-x)|I(x) - f_i(y)|^2 dy$$

Results: Steps Approaches

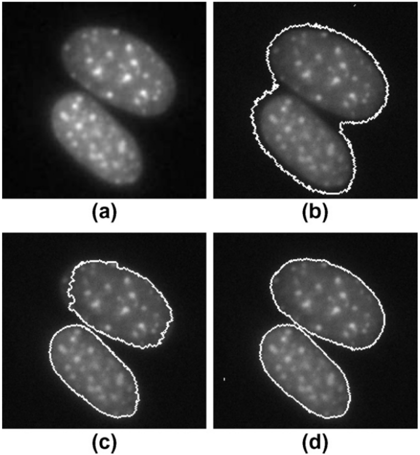


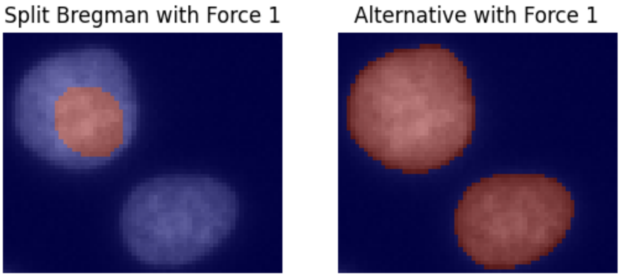
Fig. 2. Segmentation results of the three-step approach (contour overlay with original images): (a) Original image, (b) result after the first step, (c) after the second step, and (d) after the third step.

Results: Implementation Challenges

- Used a simplified version of the U20S cell dataset from a referenced article.
- Implementation Details Not Explained in the Article:
  - Normalized Level Set:
    - Clipping values at 0 and 1.
    - Utilized first-level set values to clip the image.
  - Split Bregman Algorithm:
    - Mentioned in the article but not referenced.
    - Implemented suboptimally based on provided pseudocode.
  - Gaussian Kernel Size: $(2\sigma + 1, 2\sigma + 1)$.
  - Step Approach Details:
    - Selection of α for segmenting each cell to proceed to the next step.
    - Erosion and dilation operations.

Results: Energy function Separately

Results: Test PDE Solver



Conclusion

- Published in 2012, aligns with earlier studies.
- Outdated compared to modern techniques: CNNs, RNNs, attention models, etc.
- Contributions at that time:
  - Solved level set functions as a convex problem.
  - Addressed intensity inhomogeneities using a step approach.
- Challenges and Missing Details:
  - Lack of description on problem-solving approaches.
  - Critical details missing: Gaussian kernel size, parameter d of erosion, and Gauss-Seidel algorithm parameters.
  - Specific parameters not specified hinder reproducibility.
- Our Implementation Experience:
  - Faced challenges due to insufficient article details.
  - Considered alternative methods for solving PDEs.